SWIMMING POOLS LOCALIZATION IN COLOUR HIGH-RESOLUTION SATELLITE IMAGES

C. Galindo, P. Moreno, J. González, and V. Arévalo

University of Málaga

ABSTRACT

Detecting and localizing objects from space, like roads, rivers, lakes, etc., is a challenging task with multiple applications in remote sensing. In this paper we address the detection of swimming pools in colour high-resolution images of urban areas acquired by the Quickbird satellite. The main motivation of this work is to survey and localize filled swimming pools during drought periods, fact that must be controlled by the local authorities.

The proposed algorithm applies colour analysis for water detection and approximate segmentation, as an initial, rough localization, and active contours techniques to refine the pools' shape. We have tested our algorithm in both satellite and aerial images with satisfactory results.

Index Terms— Colour high-resolution satellite images, Quickbird, Swimming-Pools localization

1. INTRODUCTION

The exploitation of satellite images is nowadays becoming relevant for ecological reasons, due to the climatic change, and it has being used for monitoring natural features like coastlines, river courses, forests, etc. In this line, one of the main problems that causes for concern in the last years is the control and management of limited and indispensable resources, as for instance potable water. Regions that undergo long periods of drought have to become aware about the moderate use of this valuable resource, striving for strictly controlling and punishing its waste. This problem is especially significant in tourist areas where a high demand of water is required to be maintained in summer, for example, for golf courses, swimming pools, waterparks, etc. This is the case of the South of Spain, where tourism is one of the major components of its economy and development, but at the same time the responsible for a great negative effect on the water reservoirs. An example of this situation can be observed in figure **??**-a) where almost every plot of land entails a private swimming pool. Bearing in mind this problem, our work strives for developing techniques for the automatic detection of open-air swimming pools which are filled up during drought periods. This would permit the local authorities to keep an inventory of the swimming pools located within its area, as well as, to impose fines to those who waste water.

Detection and localization of land features from space is a challenging task which is being addressed and exploited in the last years due to the availability of high-resolution images acquired by satellites like Quickbird or Orbview. Remote sensing applications aim to facilitate (and insofar as it is possible, to automate) monitoring tasks on large areas of terrain. Some examples can be found in the literature for detecting and locating human constructions, such as roads, buildings, sport fields, etc. (see [**?**] for a survey), plantations, e.g. of olive trees [**?**], and geographical features, like coastlines [**?**], lakes [**?**], or mountains [**?**]. Some related works to ours is [**?**, **?**] that have proposed the classification of basic terrain classes, like water or green areas in satellite images, but to the best of our knowledge, the relevant issue of the accurately detection of filled swimming pools using high resolution satellite images has not been tackled in the literature. This paper approaches this issue and proposes an algorithm that automatically detects open-air swimming pools in Quickbird satellite images of urban areas. More precisely, it considers colour analysis for detecting areas in the image with a high probability of containing water. These areas are then refined through the use of active contours. The proposed method has been tested in both satellite and aerial images with satisfactory results.

2. PROBLEM STATEMENT

The problem addressed in this work is to detect filled open-air swimming pools in colour high-resolution satellite images of urban areas. At a first glance, the automation of such a task seems to be almost trivial by searching for small rectangular blue areas in the image. Nevertheless, there are some thorny issues that turn it in a tricky problem:

- *Resolution of colour images.* Quickbird provides color images with 0.7m resolution per pixel. However, final RGB images are made from a panchromatic (grayscale) image whose resolution is effectively 0.7m, and three

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DigitalGlobe QuickBird imagery used in this study is distributed by Eurimage, SpA. (`http://www.eurimage.com`) and provided by Decasat Ingeniería S.L., Málaga, Spain. (`http://www.decasat.com`)

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Fig. 1. Example of erroneous combination of panchromatic and R,G,B bands. Note that the actual border of this swimming pool is white and not light blue as shown in the image.

Fig. 2. Irregular-shaped swimming pool.

colour images (R,G,B) whose resolution is actually 2.1m. Thus, a preprocessing of the four images is carried out to generate a 0.7m resolution colour image [**?**]. In this process, the real colour image lacks from accuracy with respect to a 0.7m resolution one, occasionally exhibiting erroneous results as shown in figure **??**.

- *Swimming Pools' shape*. Although most of swimming pools are rectangular, there are a wide variety in sizes and shapes (see for example figure **??**). Thus, the segmentation technique considered must be size and shape independent.
- *Water colour*. Images from filled swimming pools under daylight will reflect the sky and thus it will exhibit bluish tones; but, since water itself is not blue but transparent, the final colour of pixels will have a component related to the colour of the bottom of the swimming pool. There are also some issues inherent to any remote sensing application: lighting and atmospheric conditions, shadows, and reflections may alter the homogeneity of the colour. Moreover, the pool may be occluded by close objects, e.g. trees or buildings, making it not entirely visible.

3. DESCRIPTION OF THE PROPOSED METHOD

Our approach tries to overcome the aforementioned issues in a two-steps scheme. The first stage consists of a colour analysis of the image to search for homogeneous regions that, according to their colours, could correspond to swimming pools. The second stage considers the found regions and image gradient information to refine the swimming pool borders using a Snake active contours algorithm [**?**].

Figure **??** shows an overview of the proposed method.

3.1. Detecting swimming pool areas in colour images

As commented, searching for blue areas in the image is not a reliable approach for detecting water. For that we exploit the $C_1C_2C_3$ colour space [**?**], which is defined for each RGB pixel as:

Fig. 3. Scheme of the presented method explained in the text.

$$C_1 = \arctan \frac{R}{\max(G,B)} \tag{1}$$

$$C_2 = \arctan \frac{G}{\max(R,B)} \tag{2}$$

$$C_3 = \arctan \frac{B}{\max(R,G)} \tag{3}$$

In particular our approach relies on the C_1 component which has demonstrated its suitability for detecting watered areas. Alternatively, one could consider the C_3 component given its direct relation to the blue perception, but this component has a big source of false positives because of shadows which tends to be blue coloured under sunlight (see [**?**]). Thus, in our approach, we use the normalized C_1 band which yields a value between 0 and 1 as:

$$C_1 = \frac{2}{\pi} \cdot \arctan \frac{R}{\max(G,B)} \tag{4}$$

This conversion transforms the three-band image into a grayscale-like image (the C_1 band), which is then binarized applying Otsu's optimal thresholding technique [**?**]. The result of this process is a binary image composed of a black background with small white regions which very likely correspond to swimming pools (see figure **??**-b). Additionally, those regions smaller than the typical size of swimming pools are discarded since are highly probable to be false positives.

3.2. Precise shaping of swimming pools

This phase refines the actual contour of each candidate regions. To do that we extract the centroid of each region and execute a snake algorithm [**?**]. Snake algorithms adjust objects' contour by minimizing an energy function. In our case we use the following function:

$$E_{snake}\left(v\left(s\right)\right) = \int \left(\alpha \left| \frac{dv}{ds} \right|^2 + \beta \left| \frac{d^2 v}{ds^2} \right|^2 - \gamma \left| \nabla I\left(v\right) \right| \right) ds \tag{5}$$

where $\left|\nabla I\left(v\right)\right|$ represents the gradient image. This function has three weighted parameters α, β, γ, that account for the continuity of the contour, its smoothness, and the image gradient value, respectively. Experimentally those weights have been set to $\alpha = 2.5, \beta = 2.0, \gamma = 0.5$. Moreover, in our approach we consider a 110% enlargement of the candidate regions to ensure that every actual pixel of the swimming pool will be inside the contour. Concretely, we implement such an enlargement by the following transformation:

$$\begin{bmatrix} P_x \\ P_y \end{bmatrix} = \begin{bmatrix} C_x \\ C_y \end{bmatrix} + 1.1 * \begin{bmatrix} P_x - C_x \\ P_y - C_y \end{bmatrix} \tag{6}$$

where P and C represent the coordinates (x, y) of the candidates pixels and the candidate centroid, respectively. By a)

b)

c)

Fig. 4. Typical image of tourist areas in Spain. a) Quickbird image from a region in the South of Spain where almost each apartment entails a swimming pool. b) Localization of regions containing water. c) Detected swimming pools.

a) b)

c) d)

Fig. 5. Some examples of the segmented swimming pools yielded by our approach.

considering this, we overcome most of the problems derived from the resolution errors of the preprocessing of the colour images (as mentioned in section **??**).

4. EXPERIMENTAL RESULTS AND CONCLUSIONS

Our approach has been tested with Quickbird colour images of the *Costa del Sol*, in the South of Spain. The suitability of the algorithm has been contrasted with a visual localization of the swimming pools entailed in a given area, achieving excellent results: more than the 93% of the filled pools were correctly detected, failing mostly in those that exhibited occlusions and shadows.

In our tests we have initially preprocessed the input images (of 800×800 pixels) to improve the process by scaling them to twice of its original size, and applying a border highlighting filter defined by:

$$\begin{pmatrix} 0 & -0.25 & 0 \\ -0.25 & 2 & -0.25 \\ 0 & -0.25 & 0 \end{pmatrix} \tag{7}$$

Some of the localized swimming pools can be seen in figure **??**. Notice the precision of our approach to segment swimming pools of very different shapes and sizes. Also note the slight error in the segmentation of the swimming pool depicted in figure **??**-b) due to the colour resolution. Such a precision is important for estimating the correct water capacity. Nevertheless, our system is robust enough to adequately segment the close, small one. Regarding computational performance, our approach takes around 10 seconds for the considered input images using a Pentium4@2.8GHz.